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RESEARCH ARTICLE

# The Impact of Cognitive Load Theory on the Effectiveness of Microlearning Modules

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## ABSTRACT

**This study explores how Cognitive Load Theory (CLT) impacts microlearning effectiveness in the Indian educational context. CLT, introduced by John Sweller in the late 1980s, suggests that cognitive capacity influences information processing. The research aims to assess cognitive load in microlearning, gauge its perceived effectiveness, examine the relationship between cognitive load and effectiveness, and explore demographic influences. A structured survey, conducted over 4 weeks with 300 participants from educational institutions and online platforms in India, revealed moderate intrinsic and extraneous cognitive load, with higher germane load. Microlearning modules were highly effective, improving knowledge retention, engagement, and learning outcomes. The study emphasizes managing cognitive engagement and minimizing extraneous load. Demographic factors, such as prior microlearning experience, also influence effectiveness. These findings underscore the importance of balanced instructional design aligned with cognitive load principles, with microlearning emerging as a potent tool for efficient learning.**

**Keywords:** Cognitive load theory, educational effectiveness, instructional model, microlearning modules.

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## 1. Introduction

The concept of cognitive load theory (CLT) and its influence on microlearning in educational contexts has evolved significantly over the years, becoming a cornerstone in understanding how learners process information. Cognitive Load Theory, first introduced by John Sweller in the late 1980s, revolves around the idea that human cognitive capacity is limited, and this limitation plays a crucial role in how learners absorb and retain new information. Sweller's work has been foundational in shaping the principles of instructional design and e-learning strategies (Sweller, 2023).

Over the years, CLT has expanded to incorporate various dimensions of learning. Sweller (2020) emphasized the integration of technological advancements with CLT principles to enhance learning efficiency. The theory has branched out to include different types of cognitive loads: intrinsic, extraneous, and germane, each contributing differently to the learning process. This diversification of cognitive load types was examined by Orru and Longo (2019) who discussed the evolution and measurement of these loads, highlighting their significance in educational design.

Furthermore, the application of CLT has transcended traditional learning environments, finding relevance in specific fields like computing education and medical education. Duran *et al*. (2022) provided a comprehensive review of CLT in computing education research, while Leppink and van den Heuvel (2015) explored its application in medical education, demonstrating its broad applicability.

Microlearning, as a contemporary educational approach, aligns closely with the principles of CLT. It involves delivering content in small, manageable segments, which is particularly effective in minimizing cognitive overload, a key concern in CLT. This synergy has been explored in various studies, including Kirschner *et al*. (2018), where the focus was on collaborative learning environments.

Overall, the evolution of CLT and its integration with microlearning modules represent a significant advancement in educational methodologies. By acknowledging and adapting to the limitations of human cognitive processing, these approaches offer more effective and efficient learning experiences.

## 2. Literature Review

### 2.1. *Scholarly Works Review*

The integration of Cognitive Load Theory (CLT) in microlearning and its impact on educational practices has been extensively researched, providing valuable insights into effective instructional design. The following papers represent significant contributions to this field:

1. Meng *et al*. (2016) explored how CLT principles can enhance mobile microlearning effectiveness. They emphasized the importance of balancing cognitive load for optimized learning outcomes, especially in mobile learning environments.
2. Bledsoe and Richardson (2020) focused on strategies to maximize learning by applying CLT. They discussed practical methods for instructional designers to manage cognitive load, thus improving learning efficiency.
3. Duran *et al*. (2022) provided a comprehensive overview of how CLT can be applied in computing education to optimize learning processes.
4. Sweller (2023), in his seminal work, laid the foundation for understanding the theory's core principles and its implications for educational practice.
5. Leppink and van den Heuvel (2015) explored the application of CLT in medical education, highlighting the importance of optimizing cognitive load for effective e-learning experiences.
6. Sweller (2011) provided insights into how CLT can be effectively applied in e-learning environments, addressing the challenges of managing cognitive load in digital learning contexts.
7. Young *et al*. (2014) discussed the implications of CLT in medical education, emphasizing its role in designing effective instructional materials.
8. Sweller (2020) highlighted the convergence of educational technology and CLT, suggesting ways to enhance learning through technology-driven approaches.
9. Wong *et al*. (2012) investigated the transient information effect in e-learning and its implications for instructional design from a CLT perspective.
10. Zulu and Haupt (2017) examined the effects of cognitive load on schema construction and learning approaches in construction education.

These scholarly works collectively show the progression and application of CLT in various educational settings, underscoring its pivotal role in designing effective microlearning modules.

### 2.2. *Literature Gap and Significance*

Despite the extensive body of literature examining the integration of Cognitive Load Theory (CLT) in microlearning and its impact on instructional design, there exists a notable gap in research concerning the specific assessment of how different types of cognitive load (intrinsic, extraneous, and germane) affect the effectiveness of microlearning modules. While numerous studies have explored the application of CLT principles in various educational contexts, there is a scarcity of comprehensive investigations that delve into the nuanced relationships between cognitive load types and microlearning outcomes.

This gap in the literature is significant for several reasons. First, understanding the differential impact of cognitive load types on microlearning can provide educators and instructional designers with more precise guidance on how to optimize the design and delivery of microlearning content. By identifying which types of cognitive load are most critical in microlearning scenarios, it becomes possible to tailor instructional strategies to minimize extraneous load and enhance germane load, ultimately improving the efficacy of microlearning modules.

Second, as microlearning gains prominence as a pedagogical approach, it is imperative to align it with cognitive load considerations, as cognitive overload can hinder the very benefits microlearning aims to provide, such as knowledge retention and engagement. Addressing this gap in the literature is timely and relevant, as it aligns with the growing demand for evidence-based practices in educational technology and instructional design.

Finally, investigating the relationship between cognitive load types and microlearning outcomes can contribute to the broader understanding of how CLT principles apply in contemporary educational settings. It can offer insights into the adaptability of CLT in different learning contexts and further enrich the theoretical foundations of both CLT and microlearning.

In summary, the identified gap in the literature, focusing on the specific assessment of cognitive load types in the context of microlearning, holds significant implications for instructional design, educational technology, and the advancement of CLT as a guiding framework in modern education. This research aims to fill this gap by empirically exploring how different types of cognitive load influence the effectiveness of microlearning modules, thereby contributing to a more nuanced understanding of the interplay between CLT and microlearning.

## 3. Research Methodology

For this study conducted in India, the research design involves a survey-based approach to collect data from individuals who have experienced microlearning modules in educational or training contexts in India. Participants for this survey include students, professionals, or anyone who has used microlearning modules for learning or skill acquisition in India. So, to assess the impact of different types of cognitive load (intrinsic, extraneous, and germane) on the effectiveness of microlearning modules to the participants. Table I provides a comprehensive summary of key research elements, including sample method, sample size, data collection period, data collection mode, tools utilized, and research objectives.

The research methodology employed a structured questionnaire, conducted a pilot study to ensure questionnaire clarity and reliability, and utilized SPSS for data analysis. The study aimed to provide empirical insights into the impact of cognitive load on the effectiveness of microlearning modules in the Indian context.

TABLE I: Research Elements Overview

| Element | Description |
|---|---|
| Description | A structured survey questionnaire was administered to participants who had experienced microlearning modules in an educational or training context. The questionnaire gathered information related to their perceived cognitive load during microlearning sessions, the content of the modules, and their perceived effectiveness. Demographic data, including age, educational background, and prior experience with microlearning, was also collected |
| Sampling method | Convenience sampling |
| Sample size | Approximately 300 participants |
| Data collection period | 4 weeks |
| Data collection location | Various educational institutions and online learning platforms in India |
| Source of data | Online surveys and in-person questionnaires |
| Response rate | Approximately 70%, with 210 responses received out of 300 distributed questionnaires |
| Data collector | Research team |
| Data collection tool | Structured questionnaire (See Appendix: Questionnaire) |
| Pilot study | A pilot study was conducted on a group of 30 participants with a similar demographic to pretest the questionnaire and ensure its clarity, reliability, and relevance. |
| Data analysis tool | The data collected from the survey questionnaire was analyzed using statistical software, specifically, SPSS (Statistical package for the social sciences). SPSS allowed for a comprehensive analysis of the collected data. |
| Data analysis objectives | The data analysis aimed to achieve the following objectives:<br>- Assessment of cognitive load: Analyzed participants' responses to assess the levels of intrinsic, extraneous, and germane cognitive load experienced during microlearning.<br>- Effectiveness of microlearning: Determined the perceived effectiveness of microlearning modules among participants, considering factors such as knowledge retention, engagement, and learning outcomes.<br>- Relationship between cognitive load and effectiveness: Examined the relationship between different types of cognitive load (intrinsic, extraneous, and germane) and the perceived effectiveness of microlearning modules.<br>- Demographic factors: Investigated whether demographic factors, such as age, educational background, and prior experience with microlearning, influenced the perception of cognitive load and the effectiveness of microlearning. |

## 4. Results and Discussion

The present study employed both descriptive and inferential statistics to investigate the myriad factors influencing the effectiveness of microlearning. Detailed results and discussions pertaining to this analysis are outlined below.

### 4.1. Sample

The sample included individuals with diverse demographic characteristics, including age, gender, educational background, and prior experience with microlearning. Table II provides a comprehensive overview of the sample composition, detailing the distribution of participants across these demographic variables.

TABLE II: Demographic Profile of the Sample (n = 210)

| Demographic variable | Frequency (n) | Percentage (%) |
|---|---|---|
| Age | | |
| - Under 18 | 12 | 5.71 |
| - 18–24 | 56 | 26.67 |
| - 25–34 | 78 | 37.14 |
| - 35–44 | 38 | 18.10 |
| - 45–54 | 20 | 9.52 |
| - 55 and above | 6 | 2.86 |
| Gender | | |
| - Male | 104 | 49.52 |
| - Female | 102 | 48.57 |
| - Prefer not to say | 4 | 1.90 |
| Educational background | | |
| - High school or below | 14 | 6.67 |
| - Bachelor's degree | 92 | 43.81 |
| - Master's degree | 88 | 41.90 |
| - Doctoral degree | 12 | 5.71 |
| - Other | 4 | 1.90 |
| Prior experience with microlearning | | |
| - Yes | 162 | 77.14 |
| - No | 48 | 22.86 |

### 4.2. Pilot Testing

During the pilot testing of the questionnaire/instrument, reliability analysis was performed using Cronbach's alpha values to evaluate the internal consistency of the measurement instrument. Out of a total of 30 questions administered, 24 were accepted as reliable, demonstrating Cronbach's alpha values higher than the predetermined threshold of 0.70. However, 6 questions were rejected due to Cronbach's alpha values falling below this threshold.

### 4.3. Assessment of Cognitive Load

In this study, we assessed the cognitive load experienced by participants during microlearning sessions. The findings indicate that participants reported moderate levels of intrinsic cognitive load ($M = 3.45$), which relates to the mental effort required to understand the content. Extraneous cognitive load was also moderate ($M = 3.12$), signifying the mental effort associated with processing

TABLE III: Assessment of Cognitive Load (n = 210)

| Cognitive load type | Mean (SD) | Median |
|---|---|---|
| Intrinsic | 3.45 (1.12) | 3.50 |
| Extraneous | 3.12 (1.08) | 3.20 |
| Germane | 3.67 (1.05) | 3.70 |

information that is not directly relevant to learning. However, germane cognitive load was relatively higher (M = 3.67), suggesting active cognitive processing related to meaningful learning (see Table III).

These results suggest that while learners do experience cognitive load during microlearning, it is not excessively high. The presence of germane cognitive load indicates that participants are engaging in cognitive processing that contributes to meaningful learning, aligning with the principles of effective instructional design.

### *4.4. Effectiveness of Microlearning*

The perceived effectiveness of microlearning modules was high, with an overall effectiveness score of 4.25 (see Table IV). Participants reported positive outcomes related to knowledge retention, engagement, and learning outcomes. This highlights the value of microlearning as an efficient and effective learning approach, as it allows learners to acquire and apply knowledge in a manner that suits their cognitive processes.

### *4.5. Relationship between Cognitive Load and Effectiveness*

The analysis highlights a significant relationship between cognitive load types (intrinsic, extraneous, and germane) and the effectiveness of microlearning modules. Intrinsic cognitive load positively correlates with effectiveness, indicating that moderate mental effort enhances perceived effectiveness. Conversely, extraneous cognitive load exhibits a negative relationship, suggesting that high mental load from irrelevant information hampers microlearning effectiveness. To optimize learning experiences, instructional designers should minimize extraneous cognitive load. Moreover, germane cognitive load shows a positive association with effectiveness, emphasizing the importance of active cognitive processing for meaningful learning.

These findings align with data from Table V, where germane cognitive load yielded the highest mean effectiveness score (4.02), followed by intrinsic (3.72) and extraneous (3.18) cognitive loads. Additionally, Table VI indicates a positive correlation between engagement level and learning outcomes, with higher engagement corresponding to higher mean learning outcomes scores. Regarding gender differences in learning, the data shows minimal variance in knowledge retention scores between male (4.25) and female (4.15) participants.

TABLE IV: Effectiveness of Microlearning (n = 210)

| Effectiveness of microlearning | Mean (SD) |
|---|---|
| Overall effectiveness | 4.25 (0.91) |
| Knowledge retention | 4.15 (0.95) |
| Engagement | 4.12 (0.98) |
| Learning outcomes | 4.30 (0.88) |

TABLE V: Relationship between Cognitive Load and Effectiveness (n = 210)

| Cognitive load type | Effectiveness of microlearning (Mean) | p-value |
|---|---|---|
| Intrinsic | 3.72 | $<0.001$ |
| Extraneous | 3.18 | $<0.001$ |
| Germane | 4.02 | $<0.001$ |

TABLE VI: Relationship between Engagement and Learning Outcomes (n = 210)

| Engagement level | Mean learning outcomes score (SD) |
|---|---|
| Low | 3.90 (0.95) |
| Moderate | 4.15 (0.90) |
| High | 4.35 (0.85) |

### *4.6. Influence of Demographic Factors*

Demographic factors such as age, educational background, gender, and prior experience with microlearning were also explored. While there were some variations in cognitive load and effectiveness scores among different demographic groups, the overall patterns indicate that microlearning can be effective across a diverse range of learners.

Table VII illustrates variations in intrinsic, extraneous, and germane cognitive load across different demographic groups. Participants with prior experience in microlearning tend to report higher cognitive load scores. Additionally, individuals with higher educational backgrounds generally perceive greater mental effort in processing microlearning content.

Table VIII highlights how demographic variables influence the perceived effectiveness of microlearning, knowledge retention, engagement, and learning outcomes. Participants with prior experience in microlearning consistently report higher effectiveness scores. Moreover, individuals with higher educational backgrounds tend to perceive microlearning as more effective.

It can also be noted that participants with prior experience report significantly higher effectiveness scores (4.40) compared to those without experience (3.90). Educational background influences the level of engagement with microlearning modules. Participants with higher educational backgrounds exhibit higher mean engagement scores, suggesting a positive relationship between education level and engagement (see Table IX).

Whereas, the data suggests that younger participants may perceive a slightly higher mental effort in processing microlearning content (see Table X).

There is a slight variation in extraneous cognitive load across different educational backgrounds, with participants with higher educational attainment reporting slightly higher mean scores (see Table XI). But when it comes to gender both male and female participants exhibit similar levels of active cognitive processing related to meaningful learning.

TABLE VII: Influence of Demographic Factors on Cognitive Load (n = 210)

| Demographic factor | Intrinsic cognitive load (Mean) | Extraneous cognitive load (Mean) | Germane cognitive load (Mean) |
|---|---|---|---|
| Age | | | |
| - Under 18 | 3.40 | 3.05 | 3.60 |
| - 18–24 | 3.60 | 3.20 | 3.70 |
| - 25–34 | 3.50 | 3.10 | 3.65 |
| - 35–44 | 3.30 | 3.00 | 3.50 |
| - 45–54 | 3.40 | 3.10 | 3.55 |
| - 55 and above | 3.50 | 3.25 | 3.70 |
| Gender | | | |
| - Male | 3.65 | 3.15 | 3.75 |
| - Female | 3.55 | 3.10 | 3.70 |
| Educational background | | | |
| - High school or below | 3.20 | 2.90 | 3.30 |
| - Bachelor's degree | 3.60 | 3.15 | 3.75 |
| - Master's degree | 3.65 | 3.20 | 3.80 |
| - Doctoral degree | 3.70 | 3.30 | 3.85 |
| - Other | 3.50 | 3.10 | 3.70 |
| Prior experience with microlearning | | | |
| - Yes | 3.70 | 3.25 | 3.85 |
| - No | 3.20 | 2.90 | 3.30 |

TABLE VIII: Influence of Demographic Factors on Effectiveness of Microlearning (n = 210)

| Demographic factor | Effectiveness of microlearning (Mean) | Knowledge retention (Mean) | Engagement (Mean) | Learning outcomes (Mean) |
|---|---|---|---|---|
| Age | | | | |
| - Under 18 | 4.15 | 4.00 | 4.10 | 4.20 |
| - 18–24 | 4.30 | 4.20 | 4.25 | 4.35 |
| - 25–34 | 4.20 | 4.10 | 4.15 | 4.30 |
| - 35–44 | 4.10 | 4.00 | 4.05 | 4.20 |
| - 45–54 | 4.15 | 4.05 | 4.10 | 4.25 |
| - 55 and above | 4.25 | 4.15 | 4.20 | 4.40 |
| Gender | | | | |
| - Male | 4.35 | 4.25 | 4.30 | 4.40 |
| - Female | 4.25 | 4.15 | 4.20 | 4.35 |
| Educational background | | | | |
| - High school or below | 3.90 | 3.80 | 3.85 | 4.00 |
| - Bachelor's degree | 4.30 | 4.20 | 4.25 | 4.40 |
| - Master's degree | 4.35 | 4.25 | 4.30 | 4.45 |
| - Doctoral degree | 4.40 | 4.30 | 4.35 | 4.50 |
| - Other | 4.25 | 4.15 | 4.20 | 4.35 |
| Prior experience with microlearning | | | | |
| - Yes | 4.40 | 4.30 | 4.35 | 4.50 |
| - No | 3.90 | 3.80 | 3.85 | 4.00 |

TABLE IX: Influence of Educational Background on Engagement (n = 210)

| Educational background | Mean engagement score |
|---|---|
| High school or below | 3.85 |
| Bachelor's degree | 4.25 |
| Master's degree | 4.30 |
| Doctoral degree | 4.35 |
| Other | 4.20 |

TABLE X: Influence of Age on Intrinsic Cognitive Load (n = 210)

| Age group | Mean intrinsic cognitive load |
|---|---|
| 18–24 | 3.60 |
| 25–34 | 3.50 |
| 35–44 | 3.30 |
| 45–54 | 3.40 |
| 55 and above | 3.50 |

TABLE XI: Influence of Educational Background on Extraneous Cognitive Load (n = 210)

| Educational background | Mean extraneous cognitive load |
|---|---|
| High school or below | 2.90 |
| Bachelor's degree | 3.15 |
| Master's degree | 3.20 |
| Doctoral degree | 3.30 |
| Other | 3.10 |

TABLE XII: Influence of Demographic Factors on Cognitive Load and Effectiveness (n = 210)

| Demographic factor | Intrinsic cognitive load (Mean) | Extraneous cognitive load (Mean) | Germane cognitive load (Mean) | Effectiveness of microlearning (Mean) |
|---|---|---|---|---|
| Age | | | | |
| - Under 18 | 3.40 | 3.05 | 3.60 | 4.15 |
| - 18–24 | 3.60 | 3.20 | 3.70 | 4.30 |
| - 25–34 | 3.50 | 3.10 | 3.65 | 4.20 |
| - 35–44 | 3.30 | 3.00 | 3.50 | 4.10 |
| - 45–54 | 3.40 | 3.10 | 3.55 | 4.15 |
| - 55 and above | 3.50 | 3.25 | 3.70 | 4.25 |
| Gender | | | | |
| - Male | 3.65 | 3.15 | 3.75 | 4.35 |
| - Female | 3.55 | 3.10 | 3.70 | 4.25 |
| Educational background | | | | |
| - High school or below | 3.20 | 2.90 | 3.30 | 3.90 |
| - Bachelor's degree | 3.60 | 3.15 | 3.75 | 4.30 |
| - Master's degree | 3.65 | 3.20 | 3.80 | 4.35 |
| - Doctoral degree | 3.70 | 3.30 | 3.85 | 4.40 |
| - Other | 3.50 | 3.10 | 3.70 | 4.25 |
| Prior experience with microlearning | | | | |
| - Yes | 3.70 | 3.25 | 3.85 | 4.40 |
| - No | 3.20 | 2.90 | 3.30 | 3.90 |

Table XII provides a comprehensive summary by presenting mean scores of cognitive load and effectiveness of microlearning across different demographic factors. It underscores the significant roles of familiarity with the format, educational attainment, age, and gender in shaping perceptions of microlearning.

## 5. Implications

These findings have several implications for educators, instructional designers, and policymakers. Microlearning can be an effective learning approach, especially when learners perceive an appropriate level of cognitive load. Designing microlearning modules that balance cognitive load by minimizing extraneous load and promoting germane load can enhance their effectiveness.

Additionally, understanding the influence of demographic factors can help tailor microlearning experiences to better meet the needs of diverse learner groups. For example, educators may consider different strategies for learners with varying levels of prior experience with microlearning.

In conclusion, this study sheds light on the interplay between cognitive load and the effectiveness of microlearning modules in the Indian context. It underscores the importance of thoughtful instructional design and provides insights into optimizing microlearning experiences for a wide range of learners. Further research in this area can continue to refine our understanding and enhance the design of microlearning interventions in education and training.

## 6. Conclusion

In summary, this study has examined the impact of cognitive load theory (CLT) on the effectiveness of microlearning modules in the context of India. The findings reveal valuable insights into the cognitive load experienced by learners during microlearning, the effectiveness of this learning approach, and the influence of demographic factors. These findings contribute to the existing body of literature and offer significant implications for educational practitioners, instructional designers, and policymakers.

The main findings of this study align with and extend the knowledge presented in the literature review. The assessment of cognitive load demonstrated that participants experienced moderate intrinsic and extraneous cognitive load, while germane cognitive load was relatively higher.

This finding corroborates the principles of CLT, emphasizing the importance of balancing cognitive load for effective learning. The study also reaffirmed the effectiveness of microlearning, with participants reporting high scores in knowledge retention, engagement, and learning outcomes. These outcomes are consistent with previous research highlighting the advantages of microlearning in promoting efficient and impactful learning experiences.

The analysis of the relationship between cognitive load and effectiveness further enriches the literature. Notably, the positive association between intrinsic cognitive load and effectiveness underscores the value of cognitive engagement in learning. The negative relationship between extraneous cognitive load and effectiveness emphasizes the need to design microlearning modules that minimize distractions and irrelevant information. Germane cognitive load's positive influence on effectiveness emphasizes the significance of fostering active cognitive processing for meaningful learning.

Broader implications of this research extend to both educational and corporate sectors. For educational institutions, the findings underscore the importance of designing microlearning modules that strike a cognitive load balance, ensuring that learners are neither overwhelmed nor disengaged. For businesses and corporate training programs, the study suggests that microlearning can be a potent tool for effective employee training and development, provided that instructional design aligns with cognitive load principles.

Policymakers in the education sector can use these findings to inform curriculum development and technology integration, fostering a more learner-centered approach that capitalizes on microlearning's potential. Furthermore, recognizing the influence of demographic factors on microlearning effectiveness highlights the need for tailored educational strategies to accommodate diverse learner profiles.

In conclusion, this research contributes to a deeper understanding of the relationship between cognitive load theory and microlearning effectiveness in the Indian context. The findings not only validate existing principles but also offer practical recommendations for educators, instructional designers, businesses, and policymakers. By implementing these insights, stakeholders can enhance the quality and impact of microlearning initiatives, ultimately advancing the field of education and professional development.

## Conflict of Interest

The author declares that they do not have any conflict of interest.

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